To be presented at the 2nd International Workshop on Structural Health Monitoring
Stanford, CA   Sept 8-10, 1999

A Statistical Pattern Recognition Paradigm for Vibration-Based Structural Health Monitoring

Charles R. Farrar, Thomas A. Duffey, Scott W. Doebling, David A. Nix

ABSTRACT

The process of implementing a damage detection strategy for aerospace, civil and mechanical engineering systems is often referred to as *structural health monitoring*. Vibration-based damage detection is a tool that is receiving considerable attention from the research community for such monitoring. Recent research has recognized that the process of vibration-based structural health monitoring is fundamentally one of statistical pattern recognition and this paradigm is described in detail. This process is composed of four portions: 1.) Operational evaluation; 2.) Data acquisition and cleansing; 3.) Feature selection and data compression, and 4.) Statistical model development. A general discussion of each portion of the process is presented. In addition, issues associated with each portion of the process are identified and briefly discussed.

INTRODUCTION

In the most general terms damage can be defined as changes introduced into a system that adversely effect its current or future performance. Implicit in this definition is the concept that damage is not meaningful without a comparison between two different states of the system, one of which is assumed to represent the initial, and often undamaged, state. This discussion is focused on the study of damage identification in structural and mechanical systems. Therefore, the definition of damage will be limited to changes to the material and/or geometric properties of these systems, including changes to the boundary conditions and system connectivity, which adversely effect the current or future performance of that system.

Charles R. Farrar, Materials Behavior Team Leader, farrar@lanl.gov
Thomas A. Duffey, Consultant, tomd@lanl.gov
Scott W. Doebling, Technical Staff Member, doebling@lanl.gov
Los Alamos National Laboratory, Los Alamos, NM 87545
David A. Nix, research faculty, dnix@stanford.edu
Stanford Medical Center, Palo Alto, CA

The basic premise of vibration-based damage detection is that damage will significantly alter the stiffness, mass or energy dissipation properties of a system, which, in turn, alter the measured dynamic response of that system. Although the basis for vibration-based damage detection appears intuitive, its actual application poses many significant technical challenges. The most fundamental challenge is the fact that damage is typically a local phenomenon and may not significantly influence the lower-frequency global response of structures that is normally measured during vibration tests. Another fundamental challenge is that in many situations vibration-based damage detection must be performed in an *unsupervised learning* mode. Here, the term *unsupervised learning* implies that data from damaged systems are not available. These challenges are supplemented by many practical issues associated with making accurate and repeatable vibration measurements at a limited number of locations on complex structures often operating in adverse environments. Recent research has begun to recognize that the vibration-based damage detection problem is fundamentally one of statistical pattern recognition and this paradigm is described in detail.

VIBRATION-BASED DAMAGE DETECTION AND STRUCTURAL HEALTH MONITORING

The process of implementing a damage detection strategy is referred to as *structural health monitoring*. This process involves the definition of potential damage scenarios for the system, the observation of the system over a period of time using periodically spaced measurements, the extraction of features from these measurements, and the analysis of these features to determine the current state of health of the system. The output of this process is periodically updated information regarding the ability of the system to continue to perform its desired function in light of the inevitable aging and degradation resulting from the operational environments. Figure 1 shows a chart summarizing the structural health-monitoring process. The topics summarized in this figure are discussed below.

Operational Evaluation

Operational evaluation answers three questions in the implementation of a structural health monitoring system:

1.) How is damage defined for the system being investigated and, for multiple damage possibilities, which are of the most concern?
2.) What are the conditions, both operational and environmental, under which the system to be monitored functions?
3.) What are the limitations on acquiring data in the operational environment?

Operational evaluation begins to set the limitations on what will be monitored and how the monitoring will be accomplished. This evaluation starts to tailor the health monitoring process to features that are unique to the system being monitored and tries to take advantage of unique features of the postulated damage that is to be detected.

Data Acquisition and Cleansing

The data acquisition portion of the structural health monitoring process involves selecting the types of sensors to be used, selecting the location where the sensors should be placed, determining the number of sensors to be used, and defining the data acquisition/storage/transmittal hardware. This process is application specific. Economic considerations play a major role in these decisions. Another consideration is how often the data should be collected. In some cases it is adequate to collect data immediately before and at periodic intervals after a severe event. However, if fatigue crack growth is the failure mode of concern, it is necessary to collect data almost continuously at relatively short time intervals.

Because data can be measured under varying conditions, the ability to normalize the data becomes very important to the damage detection process. One of the most common procedures is to normalize the measured responses by the measured inputs. When environmental or operating condition variability is an issue, the need can arise to normalize the data in some temporal fashion to facilitate the comparison of data measured at similar times of an environmental or operational cycle. Sources of variability in the data acquisition process and with the system being monitored need to be identified and minimized to the extent possible. In general, all sources of variability cannot be eliminated. Therefore, it is necessary to make the appropriate measurements such that these sources can be statistically quantified.

Data cleansing is the process of selectively choosing data to accept for, or reject from, the feature selection process. The data cleansing process is usually based on knowledge gained by individuals directly involved with the data acquisition. Finally, it is noted that the data acquisition and cleansing portion of a structural health-monitoring process should not be static. Insight gained from the feature selection process and the statistical model development process provides information regarding changes that can improve the data acquisition process.

Feature Selection

The study of data features used to distinguish the damaged structures from undamaged ones receives considerable attention in the technical literature. Inherent in the feature selection process is the condensation of the data. The operational implementation and diagnostic measurement technologies needed to perform structural health monitoring typically produce a large amount of data. Condensation of the data is advantageous and necessary, particularly if comparisons of many data sets over the lifetime of the structure are envisioned. Also, because data may be acquired from a structure over an extended period of time and in an operational environment, robust data reduction techniques must retain sensitivity of the chosen features to the structural changes of interest in the presence of environmental noise.

The best features for damage detection are typically application specific. Numerous features are often identified for a structure and assembled into a feature vector. In general, a low dimensional feature vector is desirable. It is also desirable to obtain many samples of the feature vectors for the statistical model building portion of the study. There are no restrictions on the types or combinations of data

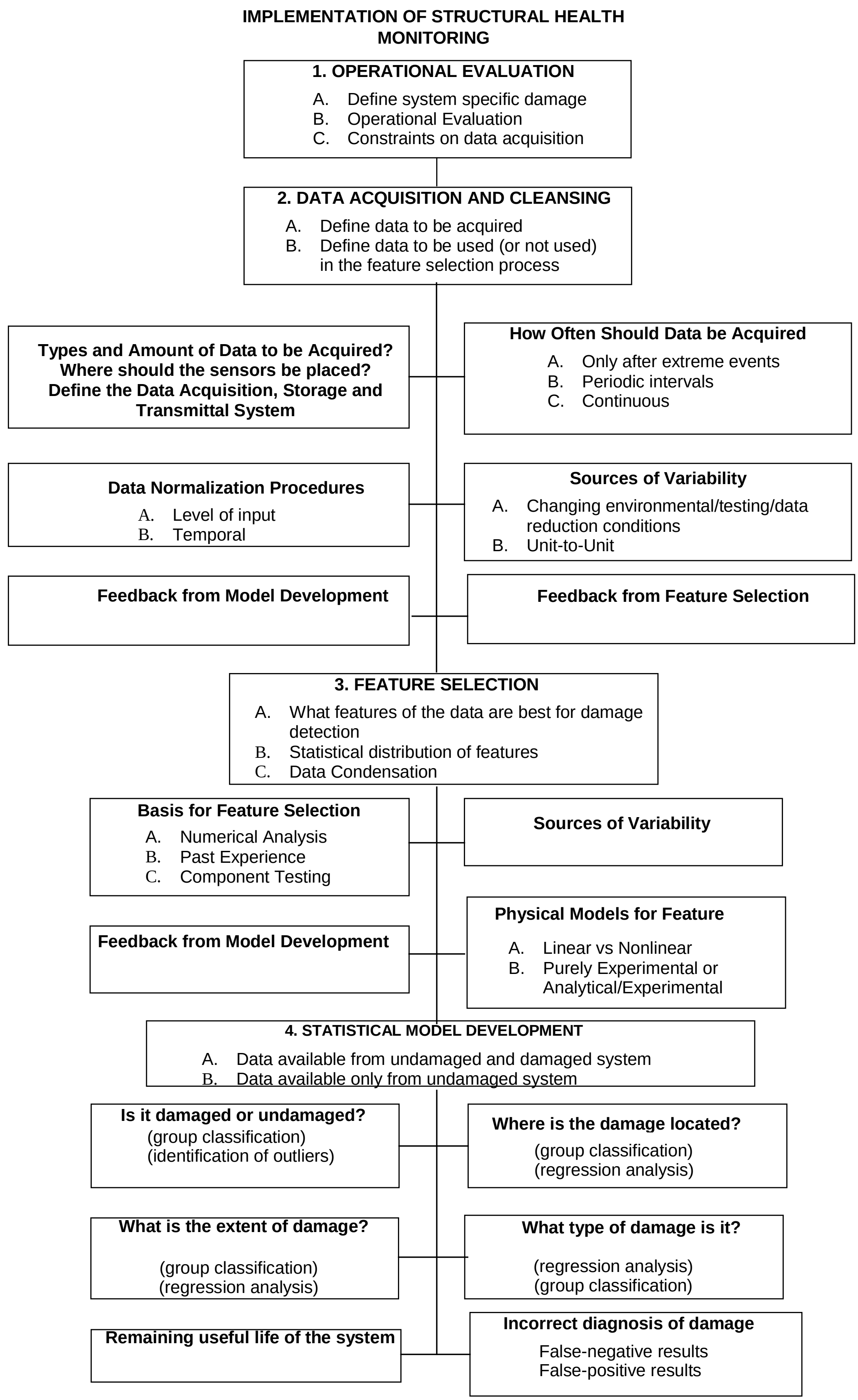

Fig. 1. Flow chart for implementing a structural health monitoring program.

contained in the feature vector. Common features used in vibration-based damage detection studies are briefly summarized below [1-3].

BASIC MODAL PROPERTIES

The most common features that are used in damage detection, and that represent a significant amount of data condensation from the actual measured quantities, are resonant frequencies and mode-shape vectors. These features are identified from measured response time-histories, most often absolute acceleration, or spectra of these time-histories. Often these spectra are normalized by spectra of the measured force input to form frequency response functions.

The amount of literature that uses resonant frequency shifts as a data feature for damage detection is large. In general, changes in frequencies cannot provide spatial information about damage. For applications to large civil engineering structures the low sensitivity of frequency shifts to damage requires either very precise measurements of frequency change or large levels of damage. An exception occurs at higher modal frequencies, where the modes are associated with local responses. However, the practical limitations involved with the excitation and identification of frequencies associated with these local modes, caused in part by high modal density and low participation factors, can make their identification difficult.

Methods that use mode shape vectors as a feature generally analyze differences between the measured modal vectors before and after damage. Mode shape vectors are spatially distributed quantities; therefore, they provide information that can be used to locate damage. However, a large number of measurement locations can be required to accurately characterize mode shape vectors and to provide sufficient resolution for determining the damage location. An alternative to using mode shapes to obtain spatially distributed features sensitive to damage is to use mode shape derivatives, such as curvature. A comparison of the relative statistical uncertainty associated with estimates of mode shape curvature, mode shape vectors and resonant frequencies showed that the largest variability is associated with estimates of mode shape curvature followed by estimates of the mode shape vector. Resonant frequencies could be estimated with least uncertainty [4].

DYNAMICALLY MEASURED FLEXIBILITY

Changes in the dynamically measured flexibility matrix indices have also been used as damage sensitive features. The dynamically measured flexibility matrix is estimated from the mass-normalized measured mode shapes and measured eigenvalue matrix (diagonal matrix of squared modal frequencies). The formulation of the flexibility matrix is approximate because in most cases all of the structure's modes are not measured. Typically, damage is detected using flexibility matrices by comparing the flexibility matrix indices computed using the modes of the damaged structure to the flexibility matrix indices computed using the modes of the undamaged structure.

UPDATING STRUCTURAL MODEL PARAMETERS

Another class of damage identification methods is based on features related to changes in mass, stiffness and damping matrix indices that have been correlated with measured dynamic properties of the undamaged and damaged structures. These methods solve for the updated matrices by forming a constrained optimization problem based on the structural equations of motion, the nominal model, and the experimentally identified modal properties [5]. Comparisons of the matrix indices that have been correlated with modal properties identified from the damaged structure to the original correlated matrix indices provide an indication of damage that can be used to quantify the location and extent of damage.

TIME-HISTORY AND SPECTRAL PATTERN METHODS

Approaches that examine changes in the features derived directly from measured time histories or their corresponding spectra have been used extensively by the rotating machinery industry. There exist numerous detailed charts of anticipated characteristic faults of a variety of machines and machine elements and corresponding features in the measured time histories or spectra [6, 7]. These features have been widely used to successfully detect the presence, location and type of fault, and the degree of damage.

Qualitative features include, for example, the presence of peaks in acceleration spectra at certain multiples of shaft rotational frequency and their growth or change with time. The important qualitative features are quite distinct to the type of machine element, the specific fault, and in some cases to the level of damage. Quantitative features fall into the following categories: time-domain methods, transformed-domain methods, and time-frequency methods. Included in transformed-domain methods are the well-known frequency-domain methods as well as the cepstrum (the inverse Fourier transform of the logarithm of the Fourier spectra magnitude squared) techniques. Briefly, frequency domain methods characterize features in machine vibrations over a given time window. Time domain and time-frequency methods have application to non-stationary faults.

TIME DOMAIN METHODS

These methods have particular application to roller bearings because these machine elements typically fail by localized defects caused by fatigue cracking and the associated removal of a piece of material on one of the bearing contact surfaces. Examples of these features include peak amplitude, rms amplitude, crest factor analysis, kurtosis analysis, and shock pulse counting.

FREQUENCY DOMAIN METHODS

Approaches applied to roller bearings include Fourier spectra of synchronized-averaged time histories, cepstrum analysis, sum and difference frequency analysis, the high frequency resonance technique, and short-time signal processing.

Quantitative evaluation gear faults has been accomplished using cepstrum peaks as a harmonic indicator. Other cepstral approaches for spectral-based fault detection have been applied to helicopter gearboxes.

TIME-FREQUENCY METHODS

These methods have their application in the investigation of rotating machinery faults exhibiting non-stationary vibration effects. Non-stationary effects are associated with machinery in which the dynamic response differs in the various phases associated with a machine cycle. Examples include reciprocating machines, localized faults in gears, and cam mechanisms. The wavelet transform has been applied to fault detection and diagnosis of cam mechanisms in and to a helicopter gearbox. A comparative study of various quantitative features that fall into the time-domain and frequency-domain categories is presented in [8].

NONLINEAR METHODS

Identification of the basic modal properties, mode shape curvature changes and dynamic flexibility are based on the assumption that a linear model represents the structural response before and after damage. However, in many cases the damage will cause the structure to exhibit nonlinear response. The specific features that indicate a system is responding in a nonlinear manner vary widely. For an extreme event such as an earthquake, the normalized Arias intensity provides an estimate of the structure's kinetic energy as a function of time and has been successfully used to identify the onset of nonlinear building response subjected to damaging excitations [9]. Deviations from a Gaussian probability distribution function of acceleration response amplitudes for a system subjected to a Gaussian input have been used successfully to identify that loose parts are present in a system. Temporal variation in resonant frequencies identified using canonical variate analysis is another method to identify the onset of damage [10]. Because all systems exhibit some degree of nonlinearity, it is a challenge to establish a threshold for which changes in the nonlinear response features are indicative of damage. Note that the previously discussed features based on time-history and spectral pattern changes are often the result of nonlinear response caused by the damage.

Statistical Model Development

The portion of the structural health monitoring process that has received the least attention in the technical literature is the development of statistical models to enhance the damage detection. Almost none of the hundreds of studies summarized in [1, 2] make use of any statistical methods to assess if the changes in the selected features used to identify damaged systems are statistically significant. However, there are many reported studies for rotating machinery damage detection applications where statistical models have been used to enhance the damage detection process.

Statistical model development is concerned with the implementation of the algorithms that operate on the extracted features to quantify the damage state of the structure. The algorithms used in statistical model development usually fall into three categories. When data are available from both the undamaged and damaged structure, the statistical pattern recognition algorithms fall into the general classification referred to as *supervised learning*. *Group classification* and *regression analysis* are general classes of algorithms for supervised learning. *Unsupervised learning* refers to algorithms that are applied to data not containing examples from the damaged structure.

The damage state of a system can be described as a five-step process along the lines of the process discussed in [11] to answers the following questions: 1. Is there damage in the system (existence)?; 2. Where is the damage in the system (location)?; 3. What kind of damage is present (type)?; 4. How severe is the damage (extent)?; and 5. How much useful life remains (prediction)? Answers to these questions in the order presented represents increasing knowledge of the damage state. The statistical models are used to answer these questions in a quantifiable manner. Experimental structural dynamics techniques can be used to address the first two questions. To identify the type of damage, data from structures with the specific types of damage must be available for correlation with the measured features. Analytical models are usually needed to answer the fourth and fifth questions unless examples of data are available from the system (or a similar system) when it exhibits varying damage levels.

Finally, an important part of the statistical model development process is the testing of these models on actual data to establish the sensitivity of the selected features to damage and to study the possibility of false indications of damage. False indications of damage fall into two categories: 1.) False-positive damage indication (indication of damage when none is present), and 2). False-negative damage indications (no indication of damage when damage is present).

SUPERVISED LEARNING: GROUP CLASSIFICATION

Group classification attempts to place the features into respective “undamaged” or “damaged” categories in a statistically quantifiable manner. Informally, skilled individuals can use their experience with previous undamaged and damaged systems and the changes in the features associated with previously observed damage cases to deduce the presence, type and level of damage. This is an example of informal *supervised learning*. For example, it is possible to examine acceleration signals in the frequency or time domain and deduce in some cases, from the presence and location of peaks, the type, location, and extent of damage of a rotating machinery component. As previously cited, extensive tables are commercially available to facilitate this process.

More formal methods founded in machine learning have been applied to damage detection. These methods place features into either an undamaged or damaged categories. The classification techniques fall into three general categories: Bayesian classifiers, K^{th}-nearest neighbor rules, and neural network classifiers [12].

SUPERVISED LEARNING: REGRESSION ANALYSIS

Another category of statistical modeling that can be employed in the damage detection process is regression analysis. Typically, this analysis refers to the process of correlating data features with particular locations or extents of damage. The features are mapped to a continuous parameter, such as spatial location or a remaining-useful-life temporal parameter, as opposed to group classification where the features correspond to discrete categories such as “damaged” or “undamaged”. Regression analysis for damage detection requires the availability of features from the undamaged structure and from the structure at varying damage levels.

UNSUPERVISED LEARNING: DENSITY ESTIMATION

Finally, analysis of outliers is employed when data are not available from a damaged structure. This type of analysis attempts to answer the question: When data from a damaged structure are not available for comparison, do the observed features indicate a significant change from the previously observed features that can not be explained by extrapolation of the feature distribution? Multivariate probability density function estimation is one of the primary statistical tools employed in this type of analysis. A particular difficulty with performing an analysis of outliers is that as the feature vectors increases in dimension, large amounts of data are needed to properly define the density function. Statistical process control is another means that can be employed to identify outliers. This approach has the advantage that it can idenity trends in the data that will allow one to predict when particular features will become outliers

CONCLUDING COMMENTS

A statistical pattern recognition paradigm for vibration-based structural health monitoring has been proposed. To date, all vibration based-damage detection methods that the authors have reviewed in the technical literature can be described by this paradigm with the vast majority of this literature focused on the identification of damage sensitive features. However, few of these studies apply statistical pattern recognition procedures to the damage-sensitive features. This lack of statistical analysis presents some potential problems for the development of vibration-based damage detection technology. As an example, the difficulties associated with accurately quantifying the statistical distribution of large order feature vectors are well documented in the statistics literature. However, most vibration-based damage detection methods discussed in the technical literature do not address this issue and many do not hesitate to suggest the use of relatively large feature vectors. A multi-disciplinary approach to the vibration-based damage detection problem is required to alleviate problems such as the “curse of dimensionality.” Such approaches offer the potential to overcome other difficulties associated with this technology such as widely varying length scales of the damage relative to that of the structure and the fact that damage can accumulate vary gradually over multi-year time scales.

Finally, a web site that is dedicated to vibration-based damage detection and that contains many of the papers and reports referenced in this study, including links to other damage detection web sites, is:
http://ext.lanl.gov/projects/damage_id/.

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